weizenbaum
DISCUSSION PAPER

Mai 2026
55

Martin Krzywdzinski

Automation and Work Through a Qualitative Lens

A Systematic Literature Review of Empirical Research from 2000 to 2024

AUTHOR

Martin Krzywdzinski \\ Weizenbaum-Institut \ martin.krzywdzinski@weizenbaum-institut.de

ABOUT THIS PAPER

This paper was written as part of the research program of the "Working with Artificial Intelligence" research group at the Weizenbaum Institute, Berlin. The research group examines the processes of designing, introducing, and using AI technologies in companies, with a focus on the associated changes in automation, job content, work organization, skill structures, and employee participation. The research program includes case studies of companies, analysis of selected issues related to human-AI cooperation in laboratory experiments, and a company survey.

ABOUT THE WEIZENBAUM INSTITUTE

The Weizenbaum Institute is a joint project funded by the German Federal Ministry of Research, Technology and Space (BMFTR) and the State of Berlin. It conducts interdisciplinary and basic research on the digital transformation of society and provides evidence- and value-based options for action in order to shape digitalization in a sustainable, self-determined and responsible manner.

Weizenbaum Discussion Paper

Automation and Work Through a Qualitative Lens

A Systematic Literature Review of Empirical Research from 2000 to 2024

Martin Krzywdzinski

Abstract

This paper presents a systematic literature review of qualitative empirical studies on the automation of work published between 2000 and 2024. It addresses three central questions: (1) What are the key findings of qualitative research on the outcomes of automation for work and their contextual and organizational determinants? (2) How do these insights compare to results from quantitative studies? (3) What gaps and future research opportunities emerge from the qualitative evidence? The review analyzes 77 studies selected from an initial pool of 4,794 publications. Using inductive coding combined with theory-driven categories, it reconstructs contextual factors (institutional regimes, sectors, occupations), input factors (technologies, managerial strategies, labor participation, organizational routines), and automation outcomes (task complexity, skill requirements, workload). The findings show no universal effects of automation; instead, outcomes vary strongly across sectors, occupational groups, and technological designs. Managerial strategies, labor power and organizational routines prove are important factors that shape the automation of work. To analyze the interaction of these factors and explain the divergent outcomes, integrating labor process theory and STS perspectives will be essential.

Contents

1 Introduction

Exactly how automation has affected work in recent years is the subject of controversial debate. The discussion is dominated by econometric studies (Acemoglu & Restrepo, 2019; Autor et al., 2020), which have presented important findings, for instance with regard to the effects of automation on the polarization of employment (Acemoglu & Restrepo, 2022; Autor et al., 2006). At the same time, these studies have their limitations. They rely on simplistic indicators of automation (e.g., number of robots or investment in equipment), or avoid directly measuring technology inputs altogether and instead merely model the impact of technology on different occupations based on certain assumptions (e.g., the routine-intensity concept (Autor et al., 2003; Bessen, 2015)). Yet, qualitative research can overcome these boundaries. With it, we are able to analyze the role of the design and implementation of different technologies for work and employment case by case. In doing so, we can take into account the particularities of the respective organizational contexts and the actual strategies of the actors involved.

However, one disadvantage of qualitative research on automation is its fragmentation. Qualitative analyses are context-specific and conducted within very different disciplinary and theoretical traditions, whose translatability is limited. This article aims to synthesize the existing results of qualitative research with the help of a systematic literature review, thereby creating a basis for drawing together diverse research results and facilitating further consolidation and development of qualitative research on automation. We will focus on the following research questions:

1. What are key findings of previous research regarding the work outcomes of automation and their determinants (context and input factors)?
2. How do the findings from qualitative research on automation of work differ from quantitative analyses?
3. What research questions and gaps are relevant for future qualitative and quantitative research on the automation of work?

This analysis follows the CIMO framework (Briner et al., 2009) by reconstructing the contextual factors of automation. It accounts for inputs or mechanisms pertaining to implementation of automation processes, as well as the outputs, i.e., the effects on work contents, and in particular on task complexity, skill requirements, and workload. This review's inductive analysis of the texts is combined with a theory-driven perspective based on recent conceptual contributions (Barley, 2020; Krzywdzinski, 2022; Thompson & Laaser, 2021). In line with the usual procedure for standardized literature reviews, this gives an overview of the state of the debate on the one hand. On the other, a special focus is placed on the differences between automation technologies and the role of organizational factors (e.g., managerial strategies), which go unconsidered in purely quantitative studies.

The systematic literature review is based on the analysis of 4794 publications spanning the years 2000–2024, from which 77 relevant sources were ultimately identified in several steps. Sources were considered relevant if they explicitly addressed processes of automation—sometimes as the main topic, sometimes as a sub-aspect. Studies that dealt with the use of technology to shape and control work processes (such as the current concept of "algorithmic management" (Kellogg et al., 2020)), but do not address automation, were excluded.

The article is structured as follows. Section 2, following the introduction, describes the procedure taken for the systematic literature review, i.e. the selection and analysis of the sources. Section 3 provides an overview of the methods and disciplines of the sources analyzed as well as the empirical fields covered (countries, sectors, technologies). Section 4 contains the core of the analysis, namely the discussion of the relationship between contextual conditions, input factors and the outcomes of automation. The article ends with conclusions.

2 Conceptual Framework, Data, and Methods

The well-known CIMO model (Briner et al., 2009) was chosen among the various other approaches available for conducting systematic literature reviews (Ilgen et al., 2005; Paul et al., 2024) to guide the analysis. CIMO distinguishes context (population, institutional frameworks, etc.), inputs (major events or developments) and mechanisms, and outcomes. The review takes an inductive approach (i.e. open coding of the selected sources) combined with theory in order to operationalize context, inputs, and outcomes. It is theory-driven in that it develops the categories of analysis based on core findings from quantitative research on automation as well as from recent conceptual contributions in the qualitative research field.

Quantitative research (for an overview see Krzywdzinski, 2025) focuses on the effects of automation on employment, productivity, and wages. Key findings include, firstly, that the impact of automation on employment is at best ambiguous — because, although jobs do become redundant, the productivity of other jobs increases; the demand for these new jobs grows; and resources are freed up for further new activities and products (Autor, 2015). Secondly, quantitative studies have emphasized that the effects of automation vary according to employee groups. Indeed, a polarization can be observed, as middle-skill routine jobs in particular are likely candidates for automation, but may also avoid automation due to falling wages (Acemoglu & Restrepo, 2022; Autor et al., 2006). Thirdly, studies have indicated that the relationship between automation and employment — and wages — is mediated not just by occupation but also by country-specific institutions and the influence of labor unions (Fernández-Macías & Hurley, 2016; Frey, 2019; Murphy & Oesch, 2018).

A primary central limitation of quantitative studies, however, is the measurement of technological change and automation. Quantitative data sets tend to only offer simplistic indicators, such as the number of robots or investments in equipment. Robots are only used in certain areas of the economy (the majority are found primarily in welding and certain assembly processes in the automotive and electronics industries as well as in transportation tasks in logistics), thus they are a rather poor indicator of automation in general (Krzywdzinski, 2021), especially with the automation of knowledge work on the horizon. For this reason, many econometric studies have switched from measuring technology or automation directly to working with model assumptions about the effects of automation on various occupations. The frequently used routine-intensity indicator is essentially based on expert assessments of the automatability of occupations (Autor, 2013, p. 201; Autor et al., 2003). Yet, many studies have relied on the indicator too heavily as a direct proxy for the impact of automation on occupations (for a critical discussion see Barley, 2020; Pfeiffer, 2016). A second central limitation of quantitative studies is that they tend to neglect of the role of actors, strategies, and routines at the organizational level. Quantitative studies usually use company size and sector as control variables, but otherwise assume the same automation logic in all companies.

Qualitative research, on the other hand, is able to overcome above-listed limitations by looking at specific technologies, their design, and their implementation. And it takes into account that actors do the choosing, designing, implementing, thereby offering a more precise examination of the very factors that cause so many difficulties for quantitative research. Qualitative research on the automation of work flourished in the 1970s and 1980s, when the focus was on the wave of factory automation (Braverman, 1974; Jürgens et al., 1993; Kern & Schumann, 1987; Noble, 1984) and on the first approaches to computerization and automation in white-collar areas (Attewell, 1987; Kraft, 1979). At that time, issues such as deskilling or upskilling, the facilitation or intensification of work through automation were the subject of heated debate. The debate subsided in the 1990s and 2000s, only to flare up again in the 2010s with the new wave of digitalization and concepts such as Industry 4.0 (Krzywdzinski, 2021). This analysis focuses on these most recent studies from the years 2000–2024.

When selecting relevant categories pertinent for a literature review, two central strands of theory are particularly useful. In the context of Labor Process Theory, *managerial strategies and labor-management power relations* have been highlighted as particularly relevant factors for the course and outcomes of automation (see the contributions in Knights & Willmott, 1990). As Thompson and Laaser (2021) have argued, these are embedded in specific accumulation regimes and modes of regulation that influence the business models of companies and the associated choice of technologies. Approaches in the tradition of Science and Technology Studies, by contrast, take a slightly different path. Barley (2020) has characterized them as a "role-based approach" (p. 63), which focuses on the particularities of *technologies* and on *organizational roles* and routines that exist in the workplace prior to automation. These approaches examine how organizational actors respond to the new technologies through their interactions and renegotiation of their roles. These roles and routines often have both a formal and an informal side, whereby the latter can differ significantly from the former.

For a review of qualitative literature on the automation of work, it is advisable to include both strands, Labor Process Theory and STS, and to focus on the following four central input factors, which directly influence the outcomes of automation:

\ Technologies, as it is a particular strength of qualitative research to address differences in the design and implementation of different automation technologies.

\ Labor participation, as power relations between labor and management, and in particular the role of employee representatives in automation processes, is a core second-order factor in Thompson and Laaser (2021) and a core influencing factor on labor-use strategies in Krzywdzinski (2022).

\ Managerial strategies, as Krzywdzinski (2022) and Thompson and Laaser (2021) see the goals, strategies, and organizational resources of management as having a significant influence on the design and implementation of technologies.

\ Organizational roles and routines, as Barley (2020) points out that the implementation of technologies and automation is influenced not only by the power relations between labor and capital but crucially also by organizational routines and the renegotiation of roles of many actors in the work process.

In addition to these four factors encompassing the implementation and mechanisms, the following analysis considers countries, sectors, and occupations as the main context factors.

The final important point is the selection of the relevant work-related outcomes of the automation to be investigated. The literature analyzed here contains a variety of concepts such as employment, task complexity, skill requirements, workload, job autonomy, and job discretion. A decision was made to omit the analysis of employment outcomes, as the manner in which this is dealt with by the quantitative literature is highly differentiated, and the new insights to be expected from qualitative research quite limited. The concepts selected for analysis were those accounted for by the majority of the identified studies. They also tended to be closely related: task complexity (discussed in 86% of identified studies), skills (70%), and workload (39%). These concepts address three different aspects of the transformation of work content through automation.

The literature review was based on records in Web of Science and Scopus as two major databases. After discussions with experts in the field, a selection of keywords—in addition to automation, including related terms (digitalization, computerization, robotization, AI, algorithmic management) –zeroed in on the focus of current debates. These are the most likely to be used in articles that examine automation. The following keywords were selected to identify the records:

\ automation OR digitalization (digitalisation) OR robotization (robotisation) OR computerization (computerisation) OR robots OR Industry 4.0 OR Fourth Industrial OR artificial intelligence OR algorithmic management AND ....

\ work OR labor (labour) AND ...

\ qualitative methods OR qualitative research OR ethnography OR case study

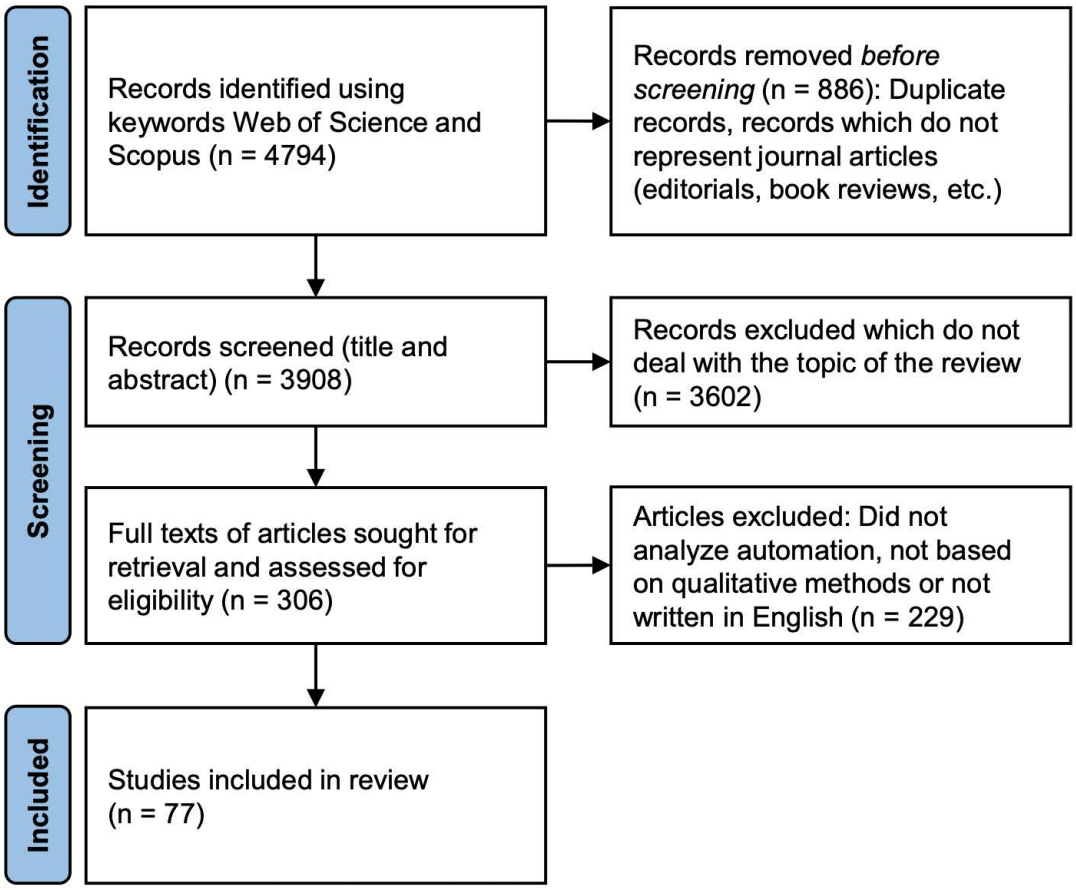
English-language journal articles from 2000–2024 were selected and only publications in the broad field of social sciences (business and management studies, behavioral sciences, sociology, political science and public administration, development studies, psychology, communication, social work, arts and humanities, cultural studies, anthropology, philosophy) were considered. The decision to concentrate the review on journal articles was deliberate, because a relatively robust quality assurance process can be assumed for scholarly literature. The author is aware that a considerable part of the research is published as working or discussion papers or related forms of publication. However, even with the focus on journal articles only, the search already yielded a large number of hits and led to the decision not to expand the search further.

As Figure 1 shows, the keywords and selection criteria used led to a total of 4794 journal article entries in Web of Science and Scopus, of which 886 were excluded before screening. The central exclusion criterion at this point was the publication type; editorials, book reviews and other forms of journal articles that did not represent original research were excluded.

A subset of 3908 articles were selected for the second step of the screening, in which the author checked the title and abstract with regard to how well each fit to the research question of the literature review. After screening, 3602 articles were excluded because they did not fit well enough to the question. This was mainly because they did not deal with the topic of automation of work or were not based on qualitative research designs and methods. The original keywords were kept intentionally broad in order to include papers that dealt with automation but did not explicitly mention the term in the abstract or title. At the same time, this unsurprisingly meant that pieces on issues of digitalization, control and optimization, or digital communication without addressing automation had to be excluded during the screening phase. Papers that examined automation processes were also excluded if they were (a) purely technical papers that tested the designs, functionality, or efficiency of the technology, or (b) purely experimental studies in the laboratory that abstracted from the questions of context and effects in real life that are central to this literature review.

Then, 306 articles were selected for full text analysis. Of these, 229 were excluded after reading the full text because (a) despite promising abstracts, they did not offer an analysis of automation processes; (b) they were not qualitative empirical research but, for example, essays, literature reviews, normative texts, or quantitative analyses of case studies; or (c) in single cases only the abstract had been translated to English but not the full text. Under (a), studies were excluded that dealt with expectations (e.g., of certain professional groups) with regard to the future effects of automation, but did not analyze actual processes or strategies of automation. A large number of studies that dealt with algorithmic management on online platforms were also categorized and excluded under (a). This is a big and separate strand of literature that focuses on automated control of platforms workers and its impacts on workload and stress, autonomy and skills, work behavior and fairness perceptions. As the work process itself is not automated (e.g., in the case of ridesharing or delivery), however, such algorithmic-management papers were excluded. All papers included in the analysis are cited in the references list and marked with an *.

Figure 1: Process of systematic literature review



The analysis process took place in several stages. In the first stage, the categories presented in section 2 were used to mark and briefly summarize passages in the analyzed texts in which statements relating to the respective categories were found. In addition, information on discipline, research, field and methods were also coded.

In the second step, the extracted categories were analyzed and a simplified measurement was developed to enable a tabular presentation in this article. For the output factors (task complexity, skill requirements, and workload), a simplified classification of the effects of automation was carried out based on the text excerpts according to a three-level scale: (a) no change or mixed outcomes, (b) reduction, (c) increase. This required a considerable simplification, as qualitative analyses often have very differentiated results. For example, if automation processes led to an increase in skill requirements for the majority of employees, an “increase” was coded, even if there was a small group that experienced a deskilling.

3 Disciplines, Journals, and Research Topics

The qualitative research literature on the automation of work revealed some characteristics worth highlighting. One major characteristic was its fragmentation. It spread across many disciplines, some of which generally make little reference to each other. The most important fields of qualitative research on the automation of work proved to be information systems/human factors and management and organization studies with 20 publications each. Sociological journals followed in third place with 19 publications. A further 18 publications spread out across a variety of other disciplines, from geography and political science to legal studies.

With regard to research methods, almost all studies combined interviews with the analysis of documents and often also observations in companies. On an abstract level, four research approaches can be distinguished (Table 1).

- The most frequently used approach can be characterized as in-depth case studies. There was a total of 36 such studies in the sample. In this approach, a small number (on average two) of company cases were examined in depth. On average, 17 interviews were conducted per case and supplemented by document analyses or observations.
- The second most common approach (27 studies) can be called short case studies. In this case, a medium number of cases (on average eight) were combined with a limited number of interviews per case (on average three).
- There were 12 ethnographies. These represented the most intensive form of data collection (on average 39 interviews that complemented longer field observation phases). The ethnographies often combined observations from a few (on average three) organizations.
- Two cases represent a historical case study that used archival sources.

Table 1: Methodological approaches in qualitative research on the automation of work, 2000–2024

Approach	No of studies	No of interviews*: Average (min-max)	No of cases: Average (min-max)	Interviews per case: Average
In-depth case studies	36	32 (10 – 100)	2 (1 – 5)	17
Short case studies	27	27 (4 – 59)	8 (1 – 25)	3
Ethnographies	12	37 (14 – 64)	3 (1 – 21)	12
Historical case studies	2	–	2	–

Note: * Nearly all studies analyzed combined interviews with analysis of documents and often workplace observations. In particular, ethnographic studies relied mainly on (participant) observation and field notes and used interviews as supplementary evidence.

The geographical distribution of the articles reflects the focus on English-language journal articles. Twenty-two studies originate from liberal market economies, with the United Kingdom in particular taking center stage with 12 studies. A second focus is Scandinavian countries, from which alone 25 studies originate. Sixteen come from Central European countries, primarily Germany and the Netherlands. In Southern Europe, Italy is a particular focus. Qualitative studies on developments in non-European countries are rare. Despite the enormous technological dynamism in Asia, only three studies could be identified with a focus on India, three with a focus on China and five with a focus on other Asian countries. There must certainly also be qualitative research on the automation of work in Asia, Africa, or South America, but it rarely finds its way into English-language journals.

In terms of sectors, it is not surprising that manufacturing played an important role (21 studies). Remarkably, however, the majority of studies dealt with white-collar sectors: finance, health and care, various professional services, public service and retail. Forty-eight of the 77 studies (62%) examined work processes in white-collar sectors; 32 (42%) analyzed blue-collar work processes.

If we take a closer look at occupational groups, there was a strong focus on professionals (ISCO 2) on the one hand with 35 studies, and on the other hand on operators and assemblers (ISCO 8) with 29 studies. Automation with a focus on service and sales workers (ISCO 5) were examined by eight studies, clerical support workers (ISCO 4) by five studies, technicians (ISCO 3) by two and laborers (ISCO 9) also by two.

With regard to the technologies examined, sectoral clusters can be identified, too, which are taken up in the subsequent analysis (Table 2). Not surprisingly, the 32 studies of manufacturing automation in general, robots (including cobots and automated guided vehicles (AGVs)) and process management systems (resource management systems, warehouse management systems, systems controlling transportation units) largely focused on the manufacturing sector and logistics. One exception was the health sector, where automated guided vehicles (AGVs) are also used and studied. Another large cluster was studies on robotic process automation (RPA), which focus primarily on the finance sector, professional services and public services. Studies on AI-based analytics and decision support systems dealt with various sectors, but focused particularly on finance and professional services. Smaller clusters were made up by studies on generative AI in the area of professional services and customer-based automation (self-checkout, self-payment systems) in retail.

Table 2: Qualitative studies of the automation of work by technology and sector, 2000–2024

	Agriculture	Finance	Health and care	Logistics and transport	Manufacturing	Professional services	Public service	Retail	Total
Manufacturing automation (general)	1	–	–	2	11	–	–	–	14
Robots and cobots	–	–	3	2	4	–	–	–	9
Process management systems	–	–	–	4	4	1	–	–	9
Scheduling and planning systems	–	–	–	1	1	–	3	–	5
Robotic process automation	–	5	–	1	1	3	6	–	16
AI-based analytics and decision support systems	1	4	2	–	1	6	–	2	16
Generative AI	–	–	–	–	–	3	–	–	3
Information provision systems	–	–	–	–	1	–	–	1	2
Customer-based automation	–	1	–	–	–	–	1	3	5
*Total**	2	10	5	10	23	13	10	6	79

Note: * Two studies include several sectors and/or technologies.

4 Contexts, Inputs, and Outcomes

Let us begin the presentation with overarching findings, based on the overview in Table 3. A first key finding is that no clear correlation arose between automation and task complexity, skills and workload; rather, what mattered was contextual factors and/or specific technology or implementation process-related factors.

4.1 Context factors

The context factors will only be briefly discussed here, as the focus of the analysis is on the input factors (technologies, managerial strategies, labor relations, organizational routines). The analysis of the role of countries as the first context variable is limited by the bias of English-language journals, which mainly contain research on automation of work in Europe. The only region that stands out here is Northern Europe, where the findings of upskilling (but also increasing workload) through automation were particularly pronounced.

The second contextual factor is sectors. Patterns in task complexity and skills did become quite clear. With regard to task complexity, four groups can be distinguished: sectors with increasing task complexity due to automation (finance and professional services), health as a sector without clear changes, sectors with decreasing task complexity (logistics, retail) and sectors with contradictory findings (manufacturing, public service). Similar patterns can be seen in the relationship between automation and skills. Some sectors' skill requirements tended to be increasing (finance, professional services); studies in the health sector showed no change; and a mixed group of sectors revealed contradictory findings (manufacturing, public service, logistics, retail).

The third context variable is occupations. In the case of professionals, the top group in the occupational hierarchy, the tendency was clear that automation has so far led to greater task complexity, upskilling, and a rather increasing workload (although the findings here are somewhat contradictory). In the case of blue-collar operators and assemblers, the trend also remained towards upskilling, although the developments proved contradictory in terms of task complexity and workload. In the case of clerical support workers and service and sales workers, the lower middle-class occupations, it is striking that a tendency towards lower task complexity and deskilling dominated. These lower-middle classes seem to be the losers of automation processes.

Table 4: Contextual factors, input factors, and outcomes

	Task complexity			Skills			Workload		
	=	-	+	=	-	+	=	-	+
Total	**24**	**16**	**24**	**15**	**10**	**26**	**6**	**10**	**13**
Context									
(i) Country groups									
› *LME*	6	3	7	7	2	3	2	1	1
› *NE*	9	2	7	2	0	9	2	3	6
› *CE*	3	4	4	4	3	5	1	2	3
› *SE*	3	3	7	1	3	7	0	2	3
› *AS*	4	3	1	2	1	2	1	2	0
› *AN*	0	1	0	0	1	0	0	0	0
(ii) Sectors									
› *Agriculture*	0	0	0	1	0	0	0	0	0
› *Finance*	2	2	6	1	2	4	2	3	0
› *Health*	4	0	1	4	0	1	0	1	2
› *Logistics*	0	5	2	0	2	3	0	1	2
› *Manufacturing*	7	5	8	4	5	9	2	2	4
› *Professional services*	7	0	3	3	0	7	1	0	1
› *Public services*	2	2	3	0	1	1	0	2	3
› *Retail*	2	3	1	2	1	1	1	1	2
(iii) Occupations									
› *Professionals*	14	2	12	6	0	13	3	4	7
› *Technicians*	1	0	1	1	1	0	0	0	0
› *Clerical support*	1	3	1	1	3	1	0	2	0
› *Service and sales*	2	3	2	2	1	1	1	2	2
› *Operators, assemblers*	5	8	7	4	4	11	2	2	4
› *Laborers*	1	0	1	1	1	0	0	0	0

Inputs									
(i) Technology									
› *Manufacturing aut.*	1	2	5	1	1	7	0	1	3
› *Robots*	5	2	1	3	2	3	1	0	1
› *Process man. systems*	1	2	3	1	1	2	0	1	2
› *Scheduling systems*	2	1	2	0	2	0	0	2	1
› *RPA*	4	1	8	0	1	6	2	3	2
› *AI-based DSS*	6	4	5	6	2	5	1	2	2
› *Generative AI*	1	0	1	0	0	3	0	0	0
› *Information provision*	1	1	0	2	0	0	2	0	0
› *Customer-based automation*	2	2	1	2	1	1	0	1	3
(ii) Participation of workers									
› *Mentioned*	11	0	10	7	1	8	1	5	2
› *Not mentioned*	13	16	14	8	9	18	5	5	11

Note: = remains the same or shows mixed developments, - is reduced, + is increased. As some studies deal with several sectors, several countries or several technologies, the sum of individual cells might be higher than the numbers indicated in "total."

4.2 Technology

Technology is first among the core input factors expected to shape the impact of automation on work. The central question here is whether qualitative research reveals differences between different technologies in terms of their impact on work.

We can make two observations here. Firstly, only a small group of technologies has so far had a relatively clear impact on work. In particular, this has been RPA — a technology used to automate data processing tasks. Studies on RPA predominantly have revealed employment to be decreasing at a time of increasing task complexity and skill requirements for the remaining workforce (Alshallaqi, 2024; Bernhard & Wihlborg, 2022; Gustafsson et al., 2024; Jain & Srinivasan, 2022; Klimkeit & Reihlen, 2022; Kokina et al., 2021; Kortesalmi et al., 2023). RPA automates repetitive tasks and leads to the upgrading of work. However, Klimkeit and Reihlen (2022) have shown in an interesting study on shared service centers in Asia and Eastern Europe how important management strategies are—we will discuss this point in-depth later. Faced with the threat of job losses due to RPA, the service centers' management began to look for more complex orders

and train employees accordingly. Without these efforts "to move up the value chain," many jobs would have been lost. The effects of RPA on workload thus seem to be contradictory (Waizenegger & Techatassanasoontorn, 2022), which is also largely related to managerial strategies and organizational routines.

What other technologies mean for the world of work is less clear. Starting with automation technologies in manufacturing, there was a difference between studies that considered manufacturing automation as a larger complex, i.e., the reorganization of larger processes through networked systems of new machines (Achtenhagen & Achtenhagen, 2019; Antonazzo et al., 2024; Cagliano et al., 2019; Hearn et al., 2023; Margherita & Braccini, 2024; Parschau & Hauge, 2020), and studies that examined the use of robots at individual workplaces. Studies that analyzed manufacturing automation as a reorganization of larger process areas tended to show task complexity on the rise and skill requirements growing due to greater complexity of the overall processes, but at the cost of increasing workload (Cagliano et al., 2019; Kadir & Broberg, 2020). Opposing developments can be seen when the focus was on standardization of tasks in the context of lean production systems (Bortolotti et al., 2023; Cirillo et al., 2021). Even stronger, however, was the trend towards decreasing task complexity in studies that analyzed the use of robots at individual workplaces (Berkers et al., 2023; Dornelles et al., 2023); while developments in skills were also contradictory (Cheon et al., 2022; Gekara & Thanh Nguyen, 2018; Moloney et al., 2024).

In the case of AI-based DSS, the findings on task complexity, skills, and workload varied greatly, which indicates that the design and actors' strategies regarding the use of the technology are crucial (Andreassen, 2020; Armour et al., 2020; Bisht et al., 2023; Borch & Hee Min, 2022; Einola & Khoreva, 2023; Gutierrez Lopez et al., 2022; Linden, 2016;Lombi & Rossero, 2024). The studies by Monod and his colleagues reported rather negative effects on employees (Monod et al., 2023, 2024), because management had used the AI systems not to support employees in decision-making and communication with customers, but for automated control and direction (see also Carreri et al., 2023). However, other studies on AI-based DSS found increasing task complexity and even job discretion (Cimini et al., 2021; Lundh & W. Rydstedt, 2016; Margherita & Braccini, 2024; Porter & Van Den Hooff, 2020). In some high-skill occupations, the implementation of AI tools has been driven by the employees themselves (Bodea et al., 2024). Applications for generative AI have so far only been studied in a few contexts, such as use by artists (Erickson, 2024) or consulting (Kronblad et al., 2024). So far, upskilling seems to dominate, but the number of qualitative studies conducted in this vein remains very small.

A special form of automation is customer-based automation, e.g., self-checkout systems in retail, which was mentioned in a few studies on public administration (i.e., application platforms for certain social benefits or services where citizens are responsible to collect and input information, which in the past was collected by case workers). Here, too, only a few studies were available, which also came to contradictory findings with regard to the effects of automation on task complexity and skills (Arkenback-Sundström, 2021; Das & Chaudhuri, 2020; Manzo et al., 2024). It is noteworthy that existing studies indicated that customer-based automation might actually increase the workload of employees. Pors and Schou (2021) explained this phenomenon in their study of the Danish public administration: When people themselves entered their own information, this automation reduced the time required by case workers to communicate

with their clients, but allowed management to increase the number of cases for workers to process. In a study from the retail sector, Moulaï et al. (2022) reported that sales staff perceive the self-checkout systems as competition and have been increasing their working speed (see Morais & Rodrigues, 2023, however, for a study that emphasized workload reduction). These contradictory findings also point to the importance of management strategies.

4.3 Labor participation

Participation takes various forms. A number of studies described processes of direct worker involvement by helping to identify use cases and application fields for automation, testing technologies, and participating in implementation (Ågnes, 2022; Becker & Hoyer, 2024; Cheon et al., 2022; Grønsund & Aanestad, 2020; Kadir & Broberg, 2020; Margherita & Braccini, 2021; Ranerup & Svensson, 2023; Van Den Broek et al., 2022; Van Hoek et al., 2022). Studies that zeroed in on workers who had participated in the implementation of automation projects consistently report fewer job losses and a more positive development of task complexity and skills. It is noteworthy that, in these studies, the increase in skill requirements and task complexity was accompanied by an increase in workload far less often, which suggests that worker participation is particularly important for designing the new performance norms appropriately. It is also striking that studies with labor participation almost never report a decrease in job discretion.

Only two of the studies evaluated in this analysis examine the integration of labor representatives in automation processes (Doellgast et al., 2023; Lloyd & Payne, 2021). Doellgast et al. (2023) compared the telecommunications industry in Norway and Germany, two cases of successful regulation of automation processes by trade unions. They showed that this regulation was based on different power resources: strong institutional participation rights in Germany and strong associational power in Norway. Lloyd and Payne (2021) compared trade union influence on the implementation of AGVs in hospitals in Norway and Scotland. They emphasized the similarities, which they attributed to the sectoral context, which overlaps country-specific differences. As hospitals belong to the public sector, trade unions were able to translate their associational power into political power and thus work towards union involvement in technology implementation. The work outcomes nevertheless showed certain country differences with a stronger upskilling dynamic in Norway.

Vereycken et al. (2024) used three case studies to develop a systematic concept for the gradual narrowing of strategic choices that occurs in the process of initiating, designing, selecting, and implementing automation projects by management. They too focused on labor participation. The decisive factor was which actors were involved in the process from the definition of goals, through the design and selection of technologies to their deployment. Labor participation was strongest when it started very early in the process.

4.4 Managerial strategies

Managerial strategies are the third core input factor. It should be noted that only a limited number of studies really addressed the development and formulation of management strategies in the context of automation processes: i.e., how decision-making processes take place in companies regarding what can be automated; which specific automation solutions are suitable; and how automation is implemented. Since this is the area with the greatest research gap, the findings of the few existing studies will be examined in more detail below in order to lay the foundation for future research.

We can distinguish between two different perspectives in the studies. The first perspective examines how different management decisions affect work with regard to the design of automation solutions. The following four dimensions of management decisions can be identified in the literature examined in this paper:

a. ***Automation of isolated tasks or reengineering of entire processes:*** In the case study of a multinational energy company, Amaya and Holweg (2024) examined automation processes in four business divisions where various applications of robotic process automation and more complex AI-based decision support systems had been introduced. According to Amaya and Holweg, the success of automation and its effects were linked to the strategy chosen by management: Where management relied on the automation of specific tasks, efficiency gains were limited, because some tasks proved to be not standardized enough. Furthermore, employees saw their jobs threatened by the substitution of these tasks and resisted technology implementation. By contrast, where management undertook automation as an element of a comprehensive reengineering of processes, the effort was much greater, but the projects had a bigger impact. In these processes, employees' tasks and roles were redesigned. This allowed more tasks to be standardized and automated, while at the same time the involvement of employees in the redesign of their roles ensured a higher acceptance of automation. Cagliano et al. (2019) examined the automation of manufacturing processes in 19 companies in Italy; they came to similar conclusions. The study revealed significantly different effects between companies that automated individual workstations and those that implemented comprehensive smart factory concepts. The automation of individual workstations usually resulted in "residual" manual activities with limited autonomy and low skill requirements remaining for the human workforce. By contrast, where comprehensive smart factory approaches were used, a fundamental reorganization of production control relied on data analysis, which in turn made it necessary to equip workers on the shop floor with data analysis skills. Although automation also led to a certain reduction in employment here, the remaining jobs tended to be upgraded.

b. ***Pure focus on efficiency or balance of efficiency and quality of work:*** While the vast majority of the studies examined in this literature review described the goal of automation to be efficiency, Berkers et al. (2023) argued in their study of the use of robots in eight warehouses that the impact on labor depended on whether management had pure efficiency goals or whether the increase in job quality was also considered when planning

automation. Job quality goals can emerge as a response to labor shortages or ergonomic process problems, for example, or due to the influence of labor power. In the Berkers et al. (2023) study, pure efficiency goals led to simplification and intensification of work, while in cases in which job quality goals were taken into account upskilling prevailed.

c. ***Technology as competitor or collaborator of human workers:*** Two studies used the introduction of robots to show two different approaches to designing the machine-human relation. Barker and Jewitt (2022) examined the use of robots in a waste sorting facility and glass manufacturing plant. In the glass company, the robot was used as a collaborator for humans to perform so-called "swabbing" tasks (brushing oil onto machines that mold molten glass into bottles). It worked alongside the human workers to reduce the amount of time the humans were exposed to the heat in this workplace, giving the workers more time to focus on planning and maintaining the machines. In the other case, the waste-sorting robot was deployed as a competitor and benchmark against which the human workers' productivity was ultimately measured. Its use led to work intensification and stress. Dornelles et al. (2023) have argued that a mere "coexistence" between humans and cobots tends to have negative effects on skills, while upskilling prevails in collaborative settings of humans and robots.

d. ***Participative or top-down introduction of technologies:*** Based on the analysis of the introduction of robotic process automation in three Swedish municipalities, Gustafsson et al. (2024) emphasized the importance of management decisions in the processes of introducing new technologies. In municipalities with a gradual and participatory introduction of RPA, the administrators took the concerns of the case workers seriously with regard to the provision of information, safeguarding human decision-making scope as well as ethical concerns. In the municipality where the introduction was abrupt and top-down, automation led to the resignation of many case workers, who felt that their professional and ethical standards were no longer guaranteed.

These four dimensions provide an initial framework for analyzing the relationship between managerial strategies and automation processes, which has to be validated and systematized in future research. The dimensions leave open the question of what drives management decisions themselves. Certainly, the contextual factors of institutional regimes and sectoral routines and standards analyzed above play an important role here. In the literature examined above, Vereycken et al. (2024) in particular emphasized, with reference to Thompson and Laaser (2021), the importance of first- and second-order choices of organizational path dependencies, which are reinforced by institutional and sectoral context factors and ultimately lead to an alignment of companies' automation strategies. Individual studies have indicated that automation processes are linked to other processes of technological change. For example, Schaupp (2022) has argued that datafication and the introduction of algorithmic management is often a precursor to automation. In addition, the following further contextual factors that influence management strategies can be identified in the literature examined:

a. ***Power relations:*** In his historical study, Hanley (2014) worked out that automation processes at General Electric were characterized by management goals of weakening or preventing union organization in the white-collar sector and the goal of strengthening management control of work processes. In an interesting analysis of the use of AI-based customer-relations assistants in sales processes, Monod et al. (2024) showed how the use of technology has changed due to management power interests. The tool was originally planned as support for sales persons. However, in the course of its use, managers learned to use the information the tool generated about work processes to strengthen control over work performance and automate sub-processes, which then led to dissatisfaction and resistance from workers. The role of historically grown power relations has also been emphasized by Vereycken et al. (2024). These power relations influence how early in the automation process labor gets involved and therefore have a significant impact on outcomes.

b. ***Conceptions of skills:*** In an analysis of the use of AI and robotics on farms in New Zealand, Legun et al. (2022) found that farmers' automation strategies were significantly influenced by the extent to which they considered embodied expertise, as opposed to technical expertise, to be important for work on the farm. Farmers promoted automation where embodied expertise was considered less relevant. Krzywdzinski and Jo (2022) have pointed out the importance of managerial conceptions of skills in a comparison between a German and a Korean automotive company. The automation strategies of the German company were influenced by relatively low status differences between skilled workers and engineers. In the Korean company, by contrast, planning and control tasks were primarily assigned to engineers and considerable status differences existed between engineers and blue-collar workers, which led to the concept of engineering-led automation.

c. ***Organizational capabilities:*** By comparing different small and medium-sized firms in Ohio, Waldman-Brown et al. (2020) have worked out how strongly automation strategies depend on the capabilities of firms. For smaller companies, extensive automation projects are hardly feasible for both financial and management reasons. In addition, these firms generally do not have expert staff, which means that the implementation of automation depends on the cooperation of skilled workers. For this reason, the firms studied by Waldman-Brown et al. relied on gradual automation, which complemented rather than substituted labor and did not challenge the social relations in the firm. A similar argument has been made by Snell and Gekara (2023) who emphasized that firms organizational and financial resources often limit the adoption of automation technologies.

4.5 Organizational routines and roles

The fourth core input factor organizational roles and practices that have evolved historically and their renegotiation in the context of automation processes. An important argument is that organizations always have a formal and an informal side. Lammi (2021) has argued that organizational structures are always only relatively loosely coupled with organizational practices and

that organizational practices are shaped by informally evolved patterns. He analyzed the introduction of a scheduling system in a Swedish insurance company and showed how the attempt to automatically control and individually assign tasks failed, because the management had ignored routines that had grown organically. Before the new scheduling system, the insurance workers had had informal ways to deviate from the assigned tasks when needed: If someone was absent, or if someone needed help from a co-worker, employees could easily share their files and tasks. The newly introduced automated system made this cooperation more difficult by assigning fixed tasks and restricting access to the respective files. This quickly led to dysfunctionalities and productivity losses, which resulted in management changing the system again, assigning tasks to entire teams who could manually decide on individual assignment and access to tasks. The desired automatic managerial control of individual performance had thus failed due to the informal organizational routines. A similar direction is revealed in studies by Lindgren et al. (2021, 2024), which dealt with the introduction of RPA in Swedish municipalities.

Organizational routines are often linked to historically evolved understanding of workers' roles, which also influences the course of automation processes. In an analysis of the failure of the introduction of RPA for performing cost calculations in a Finnish machine building company, Korhonen et al. (2020) emphasized the importance of how expertise is linked to one's understanding of their role. In this case, the engineers had previously done the price research and calculation themselves for each quotation—a task to be taken over by an RPA tool. However, the engineers did not trust the tool, because they saw price calculation as a complex process that required their own expert knowledge. They used the old and new procedures in parallel and were quickly able to show that the tool did not always use up-to-date prices because these were not always available in the relevant databases. As a result, the engineers simply gradually stopped using the tool in practice (see Viktorelius et al. (2021) for a similar case focusing on the introduction of an automatic speed control system on ferries). The study by Pors and Schou (2021), which examined the use of scheduling systems and RPA in the Danish public administration, used the concept of moral economy to examine how the role of public case workers shifted through automation. As many case decisions were automated, with citizens themselves becoming responsible for providing and entering much of the data, the case workers developed a new understanding of their role as "moral mediators", helping citizens to enter their concerns correctly into the automated systems, thereby upholding their own professional and ethical standards.

Automation can, however, create competition about occupational jurisdiction (Abbott, 1988). Andreassen (2020) used this concept to analyze the use of RPA and AI-based analysis and decision support systems in a Nordic insurance company. This development led to an increasing takeover of business analytics tasks by the managers themselves, thereby reducing the demand for management accountants. The latter responded by trying to use their analysis skills to take on tasks in areas such as customer relations or HR. This led to competition between the employee groups, and, ultimately, management accountants could not compete with the domain knowledge of workers in customer relations and HR.

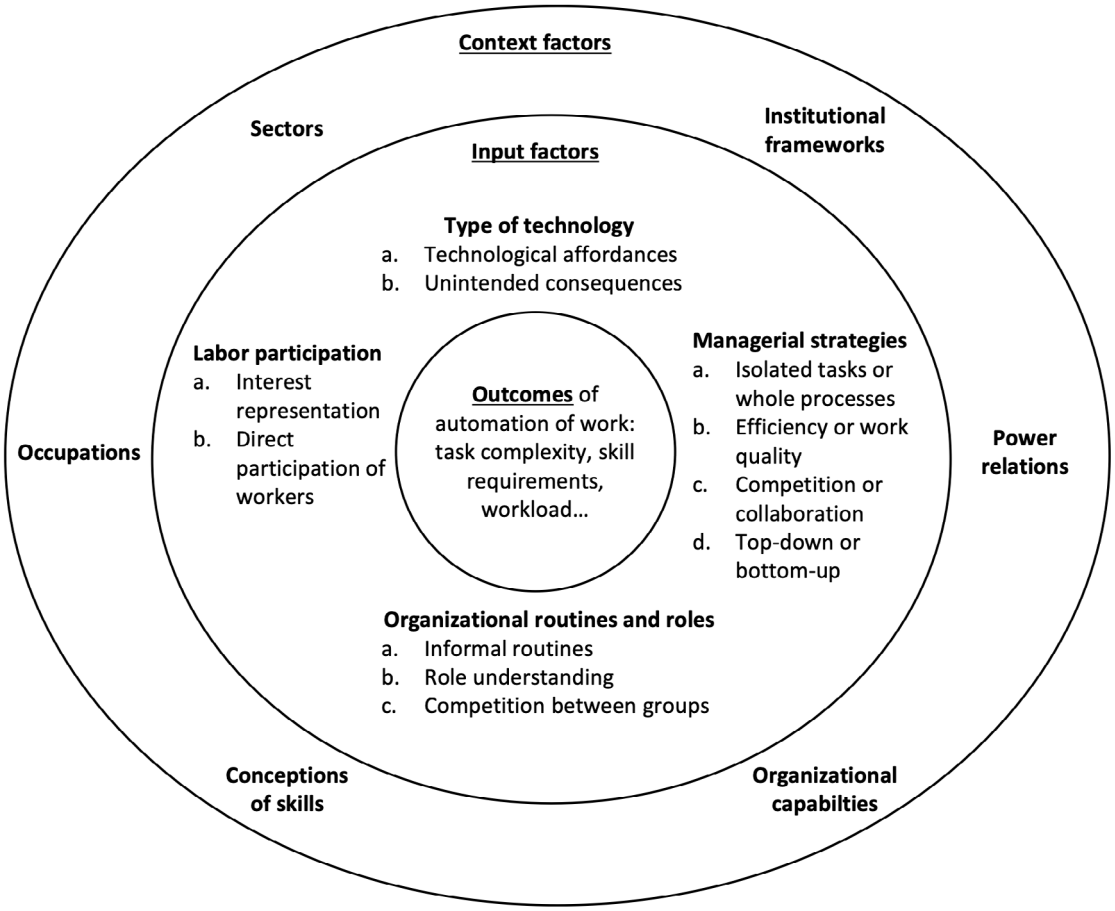
Interestingly, STS studies are the only ones to also analyze failures of automation, a topic largely neglected in other disciplinary and theoretical approaches—and extremely important for future research. We can refer to this as unintended *consequences of automation*. Papagiannidis et al. (2023) have argued that problems and shortcomings of automation solutions often only become apparent during or even after the implementation process. The authors examined a Norwegian energy company that automated its energy trading division through the use of an AI-based trading tool. The immediate effect was a reduction in the tasks and skill requirements of human energy traders, as it was assumed that the technology could act largely autonomously. The unintended consequences, however, were an increase in workload for human traders and conflicts in the organization. The technology proved to be unreliable, which meant that the traders had to invest a lot of time in correcting its mistakes (see also Balfe et al., 2012, 2018). This led to conflicts over accountability for the productivity problems and to a reintroduction of stronger human control and intensive training programs for the traders. Shestakofsky (2017) presented an interesting case study of a software company that came to recognize the limitations of its original automation plans and ultimately relied on extensive use of human labor to complement automated systems in a number of business processes. Lei (2022) illustrated the contrast between Chinese government policy, which aims to promote the adoption of advanced automation technologies, and the frustrating experiences of smaller and medium companies in China actually trying to implement these technologies.

5 Conclusions

A major contribution of this study (and answer to research question 1) has been the mapping of relevant context and input factors, summarized in Figure 2. The contextual factors include: (i) at the macro-level institutional regimes, (ii) at the meso-level sectors and occupations, and (iii) at the organizational micro-level historically grown labor-management power relations, managerial conceptions of skills, and organizational capabilities. With regard to input factors relevant in the automation processes, four groups can be distinguished: type of technology used for automation, managerial strategies in the specific automation process, labor participation, and organizational routines and roles.

The analysis clearly reveals that the relationship between automation and work outcomes is mediated by a number of factors, and the thesis of universal trends regarding deskilling or upskilling or towards increasing or decreasing task complexity and workload cannot be confirmed (see also Vereycken et al., 2024).

Figure 2: Factors influencing the impact of automation at work



With regard to research question 2, the analysis shows that there are certain similarities, but also clear differences between the qualitative research analyzed here and quantitative analyses of automation of work. There are similarities with regard to contextual factors, where qualitative research confirms some of the findings of quantitative analyses, in particular the importance of sector and occupation. Sectors and occupational groups in which qualitative studies tend to report increasing task complexity and upskilling are: professionals in general, and finance and professional services as specific sectors. In contrast, a reduction in task complexity and deskilling tends to be reported in the logistics and retail sectors, as well as for clerical workers and sales and services workers. If we regard these latter occupations as classic white-collar middle classes, the findings of the qualitative studies reverberate with the polarization argument due to automation effects made in quantitative research (Goos et al., 2009). These middle occupational segments could be most affected by the negative consequences of automation.

Clear differences between qualitative and quantitative research become apparent when analyzing input factors in automation processes. Quantitative studies ignore the particularities of technologies, managerial strategies, labor involvement, and organizational routines; whereas, qualitative studies show them to be decisive for the outcomes of automation in the workplace.

An important conclusion to be drawn here is that concepts from both the field of labor studies and the field of STS offer important contributions and should be combined more closely in future research. In labor studies, and especially in the tradition of labor process theory, it is common to assign a central role to labor agency, with a particular focus on the organizational power and resistance of labor against managerial strategies. At a general level, the present analysis confirms the emphasis on the importance of labor. The involvement of labor proves to be a central factor that reduces negative employment and workload effects in automation processes and, ultimately, promotes upskilling. However, this factor cannot be reduced to resistance alone. A number of qualitative studies describe the active involvement of workers in shaping automation as a factor that leads to positive effects of automation on work (Ågnes, 2022; Becker & Hoyer, 2024; Cheon et al., 2022; Grønsund & Aanestad, 2020; Van Den Broek et al., 2022). A core question is at what point in time in the implementation of automation the labor involvement takes place (Vereycken et al., 2024). Two studies have addressed the role of collective interest representation, but only emphasized the negotiation and compromise processes involved (Doellgast et al., 2023; Lloyd & Payne, 2021). Resistance to automation has been a topic primarily examined in STS studies and thus discussed not in the context of management-labor power relations but rather in the persistence of organizational roles and routines in the face of technical change (Viktorelius et al., 2021).

Another factor emphasized by studies in the context of labor process theory is managerial strategies (Thompson & Laaser, 2021). Despite the emphasis on this factor, however, research largely lacks concepts that help distinguish between different managerial strategies in the use of technology in the workplace (Vidal, 2022). An important contribution of the present literature review has therefore been to distinguish between different dimensions of managerial strategies identified in empirical research: Work outcomes of automation differ significantly depending on (1) whether management automates individual tasks in isolation or undertakes the reengineering of entire processes (Amaya & Holweg, 2024; Cagliano et al., 2019); (2) whether there is a pure focus on efficiency or whether other goals of automation are also taken into account (Berkers et al., 2023); (3) whether technology is used as a collaborator of human workers or specifically as a competitor (Barker & Jewitt, 2022; Dornelles et al., 2023); and (4) what strategy management pursues when involving actors in automation processes (Vereycken et al., 2024). These dimensions of management strategies have been identified inductively in existing empirical research—a more systematic framework is still to be developed (research question 3). This framework should also consider the role of technologies and the organizational routines beyond the labor-management conflict, a field in which labor studies can learn from STS (Howcroft & Taylor, 2023). More systematic research is also needed regarding the determinants of managerial strategies. The empirical studies included in this review point to labor-management power relations, managerial conceptions of skills and organizational capabilities; however, they consider each of these factors individually and do not undertake a systematic exploration of determinants of automation strategies.

Studies in the STS tradition tend to focus on technologies and their negotiation in the context of given organizational routines and roles. Interestingly, the present literature review shows that only a few technologies show clear patterns regarding work outcomes: RPA as a very narrow automation technology leads to the automation of repetitive data processing tasks, while the work content tends to experience an increase in complexity and skill requirements. The other technologies discussed in the literature, on the other hand, have very different effects on work, depending on the organizational context.

Core concepts for analyzing the organizational context are informal organizational routines (Lammi, 2021) and how professional groups understand their roles (Korhonen et al., 2020; Viktorelius et al., 2021), especially if these professional groups occupy a strong position in the organization due to their expertise and ability to mobilize. Automation processes set in motion a renegotiation of roles, which can also lead to competition between groups (Andreassen, 2020). The tensions between automation and organizational routines and roles can have unintended consequences—a topic that has so far only been addressed by a few studies and represents a significant research gap (Amaya & Holweg, 2024; Korhonen et al., 2020; Papagiannidis et al., 2023; Wright, 2019). Several studies mention unexpected problems of automation as central factors that led its association with increasing workload and stress (Körner et al., 2019; Kouroutzas & Palamari, 2025; Papagiannidis et al., 2023). The significance of such automation failures has been underestimated in research to date, and systematic investigation of them is still pending. STS would benefit from adopting a more precise focus on management strategies and management-labor conflicts from labor studies. When it comes to automation failures, the decisions made by management regarding specific approaches to automation play a major role.

Finally, it should be noted that quantitative analyses can also benefit from the findings of qualitative research. The first important point is that it makes very little sense to view technology as a homogeneous entity and measure it using a single variable (e.g., robots or financial indicators for investments in equipment or IT). There are surveys that distinguish between different types of technologies (Arntz et al., 2025), and such surveys should be developed further and used more widely. Second, it makes sense to consider whether variables can be developed that measure types of management strategies and types of labor involvement more accurately and thus provide greater insight into organizational processes. The most difficult aspect, and one that is virtually impossible to achieve in quantitative studies, is the consideration of informal organizational processes, negotiations, and conflicts at the shop floor level. For this reason, the combination of qualitative and quantitative analyses will continue to be central to understanding the automation of work.

References

Abbott, A. (1988). *The System of Professions. An Essay on the Division of Expert Labor*. University of Chicago Press.

Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives, 33*(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., & Restrepo, P. (2022). Tasks, Automation, and the Rise in U.S. Wage Inequality. *Econometrica, 90*(5), 1973–2016. https://doi.org/10.3982/ECTA19815

*Achtenhagen, C., & Achtenhagen, L. (2019). The impact of digital technologies on vocational education and training needs: An exploratory study in the German food industry. *Education + Training, 61*(2), 222–233. https://doi.org/10.1108/ET-05-2018-0119

*Ågnes, J. S. (2022). Gaining and Training a Digital Colleague: Employee Responses to Robotization. *The Journal of Applied Behavioral Science, 58*(1), 29–64. https://doi.org/10.1177/00218863211043596

*Alshallaqi, M. (2024). The complexities of digitization and street-level discretion: A socio-materiality perspective. *Public Management Review, 26*(1), 25–47. https://doi.org/10.1080/14719037.2022.2042726

*Amaya, J., & Holweg, M. (2024). Using algorithms to improve knowledge work. *Journal of Operations Management, 70*(3), 482–513. https://doi.org/10.1002/joom.1296

*Andreassen, R.-I. (2020). Digital technology and changing roles: A management accountant's dream or nightmare? *Journal of Management Control, 31*(3), 209–238. https://doi.org/10.1007/s00187-020-00303-2

*Antonazzo, L., Stroud, D., & Weinel, M. (2024). Smart manufacturing and tasks automation in the steel industry: Reflecting on routine work and skills in Industry 4.0. *Economic and Industrial Democracy, 45*(3), 914–936. https://doi.org/10.1177/0143831X231201002

*Arkenback-Sundström, C. (2021). A Postdigital Perspective on Service Work: Salespeople's Service Encounters in the Connected Store. *Postdigital Science and Education, 4*(2), 422–446. https://doi.org/10.1007/s42438-021-00280-2

*Armour, J., Parnham, R., & Sako, M. (2020). Augmented Lawyering. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3688896

Arntz, M., Baum, M., Brüll, E., Dorau, R., Lehmer, F., Matthes, B., Meyer, S.-C., Schlenker, O., Tisch, A., & Wischniewski, S. (2025). *Digital Transformation and the Changing World of Work (DiWaBe 2.0): A Data Source for Research on Artificial Intelligence and Other Technologies in the Workplace*. Bundesanstalt für Arbeitsschutz und Arbeitsmedizin (BAuA). https://doi.org/10.21934/BAUA:BERICHT20250319

Attewell, P. (1987). Big Brother and the Sweatshop: Computer Surveillance in the Automated Office. *Sociological Theory, 5*(1), 87. https://doi.org/10.2307/201997

Autor, D. H. (2013). The "task approach" to labor markets: An overview. *Journal for Labour Market Research, 46*(3), 185–199. https://doi.org/10.1007/s12651-013-0128-z

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives, 29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The Polarization of the U.S. Labor Market. *American Economic Review, 96*(2), 189–194. https://doi.org/10.1257/000282806777212620

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics, 118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Autor, D. H., Mindell, D., & Reynolds, E. (2020). T*he Work of the Future: Building Better Jobs in an Age of Intelligent Machines* [Final Report of the MIT Work of the Future Taskforce]. MIT. https://workofthefuture.mit.edu/wp-content/uploads/2021/01/2020-Final-Report4.pdf

*Balfe, N., Sharples, S., & Wilson, J. R. (2018). Understanding Is Key: An Analysis of Factors Pertaining to Trust in a Real-World Automation System. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 60*(4), 477–495. https://doi.org/10.1177/0018720818761256

*Balfe, N., Wilson, J. R., Sharples, S., & Clarke, T. (2012). Development of design principles for automated systems in transport control. *Ergonomics, 55*(1), 37–54. https://doi.org/10.1080/00140139.2011.636456

*Barker, N., & Jewitt, C. (2022). Filtering Touch: An Ethnography of Dirt, Danger, and Industrial Robots. *Journal of Contemporary Ethnography, 51*(1), 103–130. https://doi.org/10.1177/08912416211026724

Barley, S. R. (2020). *Work and Technological Change*. Oxford University Press.

*Becker, B., & Hoyer, P. (2024). The anatomy of clinical decision-making: Aligning AI design with ICU routines. *Journal of Organizational Ethnography, 13*(3), 427–451. https://doi.org/10.1108/JOE-03-2024-0011

*Berkers, H. A., Rispens, S., & Le Blanc, P. M. (2023). The role of robotization in work design: A comparative case study among logistic warehouses. *The International Journal of Human Resource Management, 34*(9), 1852–1875. https://doi.org/10.1080/09585192.2022.2043925

*Bernhard, I., & Wihlborg, E. (2022). Bringing all clients into the system – Professional digital discretion to enhance inclusion when services are automated. *Information Polity, 27*(3), 373–389. https://doi.org/10.3233/IP-200268

Bessen, J. E. (2015). How Computer Automation Affects Occupations: Technology, Jobs, and Skills. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2690435

*Bisht, N. S., Trusson, C., Siwale, J., & Ravishankar, M. N. (2023). Enhanced job satisfaction under tighter technological control: The paradoxical outcomes of digitalisation. *New Technology, Work and Employment, 38*(2), 162–184. https://doi.org/10.1111/ntwe.12222

*Bodea, C.-N., Paparic, M., Ioan Mogoș, R., & Dascălu, M.-I. (2024). Artificial Intelligence Adoption in the Workplace and Its Impact on the Upskilling and Reskilling Strategies. *Amfiteatru Economic, 26*(65), 126. https://doi.org/10.24818/EA/2024/65/126

*Borch, C., & Hee Min, B. (2022). Toward a sociology of machine learning explainability: Human–machine interaction in deep neural network-based automated trading. *Big Data & Society, 9*(2), 20539517221111361. https://doi.org/10.1177/20539517221111361

*Bortolotti, T., Boscari, S., Morton, E., & Powell, D. (2023). Integrating Smart Manufacturing to Lean: A Multiple-Case Study of the Impact on Shop-Floor Employees' Autonomy and Empowerment. *Advances in Production Management Systems 689*, 109–124. https://doi.org/10.1007/978-3-031-43662-8_9

Braverman, H. (1974). *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century*. Monthly Review.

Briner, R. B., Denyer, D., & Rousseau, D. M. (2009). Evidence-Based Management: Concept Clean-up Time? *Academy of Management Perspectives, 23*(4), 19–32. https://doi.org/10.5465/amp.23.4.19

*Cagliano, R., Canterino, F., Longoni, A., & Bartezzaghi, E. (2019). The interplay between smart manufacturing technologies and work organization: The role of technological complexity. *International Journal of Operations & Production Management, 39*(6/7/8), 913–934. *https://doi.org/10.1108/IJOPM-01-2019-0093*

*Carreri, A., Gosetti, G., & Masiero, N. (2023). Digitalization of relational space in the service triangle: The case study of retail banking. *Frontiers in Sociology, 8*, 1141879. https://doi.org/10.3389/fsoc.2023.1141879

*Cheon, E., Schneiders, E., & Skov, M. B. (2022). Working with Bounded Collaboration: A Qualitative Study on How Collaboration is Co-constructed around Collaborative Robots in Industry. *Proceedings of the ACM on Human-Computer Interaction, 6*(CSCW2), 1–34. https://doi.org/10.1145/3555094

*Cimini, C., Lagorio, A., Pirola, F., & Pinto, R. (2021). How human factors affect operators' task evolution in Logistics 4.0. *Human Factors and Ergonomics in Manufacturing & Service Industries, 31*(1), 98–117. https://doi.org/10.1002/hfm.20872

*Cirillo, V., Rinaldini, M., Staccioli, J., & Virgillito, M. E. (2021). Technology vs. workers: The case of Italy's Industry 4.0 factories. *Structural Change and Economic Dynamics, 56*, 166–183. https://doi.org/10.1016/j.strueco.2020.09.007

*Das, S., & Chaudhuri, B. (2020). In Technology We Trust? Human Skills & Intermediaries in Digital Retail Banking. *International Federation for Information Processing AICT* 601, 281–294. https://doi.org/10.1007/978-3-030-64697-4_21

*Doellgast, V., Wagner, I., & O'Brady, S. (2023). Negotiating limits on algorithmic management in digitalised services: Cases from Germany and Norway. *Transfer: European Review of Labour and Research, 29*(1), 105–120. https://doi.org/10.1177/10242589221143044

*Dornelles, J. D. A., Ayala, N. F., & Frank, A. G. (2023). Collaborative or substitutive robots? Effects on workers' skills in manufacturing activities. *International Journal of Production Research, 61*(22), 7922–7955. https://doi.org/10.1080/00207543.2023.2240912

*Einola, K., & Khoreva, V. (2023). Best friend or broken tool? Exploring the co-existence of humans and artificial intelligence in the workplace ecosystem. *Human Resource Management, 62*(1), 117–135. https://doi.org/10.1002/hrm.22147

*Erickson, K. (2024). AI and work in the creative industries: Digital continuity or discontinuity? *Creative Industries Journal*, 1–21. https://doi.org/10.1080/17510694.2024.2421135

Fernández-Macías, E., & Hurley, J. (2016). *Routine-biased technical change and job polarization in Europe. Socio-Economic Review, 15*(3), 563–585. https://doi.org/10.1093/ser/mww016

Frey, C. B. (2019). *The Technology Trap: Capital, Labor, and Power in the Age of Automation*. Princeton University Press.

*Gekara, V. O., & Thanh Nguyen, V. (2018). New technologies and the transformation of work and skills: A study of computerisation and automation of Australian container terminals. *New Technology, Work and Employment, 33*(3), 219–233. https://doi.org/10.1111/ntwe.12118

Goos, M., Manning, A., & Salomons, A. (2009). Job Polarization in Europe. *American Economic Review, 99*(2), 58–63. https://doi.org/10.1257/aer.99.2.58

*Grønsund, T., & Aanestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *The Journal of Strategic Information Systems, 29*(2), 101614. https://doi.org/10.1016/j.jsis.2020.101614

*Gustafsson, M. S., Kazlou, A., & Wihlborg, E. (2024). Automation in Social Care: A Case Study of Organizational Challenges and Skills Dynamics in Three Swedish Municipalities. *Electronic Government, 2024*, 218–233. https://doi.org/10.1007/978-3-031-70274-7_14

*Gutierrez Lopez, M., Porlezza, C., Cooper, G., Makri, S., MacFarlane, A., & Missaoui, S. (2022). A Question of Design: Strategies for Embedding AI-Driven Tools into Journalistic Work Routines. *Digital Journalism, 11*(3), 484–503. https://doi.org/10.1080/21670811.2022.2043759

*Hanley, C. (2014). Putting the Bias in Skill-Biased Technological Change? A Relational Perspective on White-Collar Automation at General Electric. *American Behavioral Scientist, 58*(3), 400–415. https://doi.org/10.1177/0002764213503339

*Hearn, G., Williams, P., Rodrigues, J. H. P., & Laundon, M. (2023). Education and training for industry 4.0: A case study of a manufacturing ecosystem. *Education+ Training, 65*(8–9), 1070–1084. https://doi.org/10.1108/ET-10-2022-0407

Howcroft, D., & Taylor, P. (2023). Automation and the future of work: A social shaping of technology approach. *New Technology, Work and Employment, 38*(2), 351–370. https://doi.org/10.1111/ntwe.12240

Ilgen, D. R., Hollenbeck, J. R., Johnson, M., & Jundt, D. (2005). Teams in Organizations: From Input-Process-Output Models to IMOI Models. *Annual Review of Psychology, 56*(1), 517–543. https://doi.org/10.1146/annurev.psych.56.091103.070250

*Jain, A., & Srinivasan, V. (2022). What happened to the work I was doing? Sociomateriality and cognitive tensions in technology work. *Organizational Dynamics, 51*(4). https://doi.org/10.1016/j.orgdyn.2022.100901

Jürgens, U., Malsch, T., & Dohse, K. (1993). *Breaking with Taylorism. Changing Forms of Work in the Automobile Industry*. Cambridge University Press.

*Kadir, B. A., & Broberg, O. (2020). Human well-being and system performance in the transition to industry 4.0. *International Journal of Industrial Ergonomics, 76*, 102936. https://doi.org/10.1016/j.ergon.2020.102936

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at Work: The New Contested Terrain of Control. *Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Kern, H., & Schumann, M. (1987). Limits of the Division of Labour. New Production and Employment Concepts in West German Industry. *Economic and Industrial Democracy, 8*(2), 151–170. https://doi.org/10.1177/0143831X8782002

*Klimkeit, D., & Reihlen, M. (2022). No longer second-class citizens: Redefining organizational identity as a response to digitalization in accounting shared services. *Journal of Professions and Organization, 9*(1), 115-138. https://doi.org/10.1093/jpo/joac003

Knights, D., & Willmott, H. (Eds.). (1990). *Labour Process Theory*. Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-20466-3

*Kokina, J., Gilleran, R., Blanchette, S., & Stoddard, D. (2021). Accountant as Digital Innovator: Roles and Competencies in the Age of Automation. *Accounting Horizons, 35*(1), 153–184. https://doi.org/10.2308/HORIZONS-19-145

*Korhonen, T., Selos, E., Laine, T., & Suomala, P. (2020). Exploring the programmability of management accounting work for increasing automation: An interventionist case study. *Accounting, Auditing & Accountability Journal, 34*(2), 253–280. https://doi.org/10.1108/AAAJ-12-2016-2809

*Körner, U., Müller-Thur, K., Lunau, T., Dragano, N., Angerer, P., & Buchner, A. (2019). Perceived stress in human–machine interaction in modern manufacturing environments—Results of a qualitative interview study. *Stress and Health, 35*(2), 187–199. https://doi.org/10.1002/smi.2853

*Kortesalmi, H., Aunimo, L., & Kedziora, D. (2023). RPA Experiments in SMEs through a Collaborative Network. *Collaborative Networks in Digitalization and Society 5.0, 688*. https://doi.org/10.1007/978-3-031-42622-3_54

*Kouroutzas, C., & Palamari, V. (2025). Opening the black boxes of the black carpet in the era of risk society: A sociological analysis of AI, algorithms and big data at work through the case study of the Greek postal services. *AI & SOCIETY, 40*(2), 825–838. https://doi.org/10.1007/s00146-024-01916-0

Kraft, P. (1979). The Routinizing of Computer Programming. *Sociology of Work and Occupations, 6*(2), 139–155. https://doi.org/10.1177/009392857962002

*Kronblad, C., Jonsson, A., & Pemer, F. (2024). Generative AI Beyond the Hype—New Technologies in the Face of Organizing and Organizations. *The Journal of Applied Behavioral Science, 60*(4), 623–630. https://doi.org/10.1177/00218863241285454

Krzywdzinski, M. (2021). Automation, digitalization, and changes in occupational structures in the automobile industry in Germany, Japan, and the United States: A brief history from the early 1990s until 2018. *Industrial and Corporate Change, 30*(3), 499–535. https://doi.org/10.1093/icc/dtab019

Krzywdzinski, M. (2022). Toward a Socioeconomic Company-Level Theory of Automation at Work. *Weizenbaum Journal of the Digital Society, 2*(1), 1–29. https://doi.org/10.34669/WI.WJDS/2.1.5

Krzywdzinski, M. (2025). Automation, artificial intelligence and the future of work. In J. Heyes, J. Leschke, K. Newsome, M. Reich, & A. Wilkinson (Eds.), *Research Handbook on Decent Work in a Post-COVID-19 World* (pp. 86–100). Edward Elgar Publishing. https://doi.org/10.4337/9781800882751.00012

*Krzywdzinski, M., & Jo, H. J. (2022). Skill formation, automation and governance: Comparing German and Korean automotive manufacturers in Central-Eastern Europe. *Critical Perspectives on International Business, 18*(1), 115–136. https://doi.org/10.1108/cpoib-02-2020-0007

*Lammi, I. J. (2021). Automating to control: The unexpected consequences of modern automated work delivery in practice. *Organization, 28*(1), 115–131. https://doi.org/org/10.1177/1350508420968179

*Legun, K., Burch, K. A., & Klerkx, L. (2022). Can a robot be an expert? The social meaning of skill and its expression through the prospect of autonomous AgTech. *Agriculture and Human Values, 40*(2), 501–517. https://doi.org/10.1007/s10460-022-10388-1

*Lei, Y.-W. (2022). Upgrading China through Automation: Manufacturers, Workers and the Techno-Developmental State. *Work, Employment and Society, 36*(6), 1078–1096. https://doi.org/10.1177/0950017021999198

*Linden, C.-G. (2016). Decades of Automation in the Newsroom. *Digital Journalism, 5*(2), 123–140. https://doi.org/10.1080/21670811.2016.1160791

*Lindgren, I., Toll, D., Johansson, B., Booth, M., Rizk, A., & Melin, U. (2024). Organizational conditions required to implement RPA in local government. *Proceedings of the 25th Annual International Conference on Digital Government Research*, 434–442. https://doi.org/10.1007/978-3-031-70274-7_17

*Lindgren, I., Toll, D., & Melin, U. (2021). Automation as a Driver of Digital Transformation in Local Government. *Dg.o '21: Proceedings of the 22nd Annual International Conference on Digital Government Research*, 463–472. https://doi.org/10.1145/3463677.3463685

*Lloyd, C., & Payne, J. (2021). Fewer jobs, better jobs? An international comparative study of robots and 'routine' work in the public sector. *Industrial Relations Journal, 52*(2), 109–124. https://doi.org/10.1111/irj.12323

*Lombi, L., & Rossero, E. (2024). How artificial intelligence is reshaping the autonomy and boundary work of radiologists. A qualitative study. *Sociology of Health & Illness, 46*(2), 200–218. https://doi.org/10.1111/1467-9566.13702

*Lundh, M., & W. Rydstedt, L. (2016). A static organization in a dynamic context—A qualitative study of changes in working conditions for Swedish engine officers. *Applied Ergonomics, 55*, 1–7. https://doi.org/10.1016/j.apergo.2016.01.006

*Manzo, C., Fullin, G., & Bianconi, B. (2024). Work and Technological Innovation in the Retail Sector. The Case of Fast Fashion Stores in Italy. *Italian Sociological Review*, 979-1002. https://doi.org/10.13136/ISR.V14I3.794

*Margherita, E. G., & Braccini, A. M. (2021). Managing Industry 4.0 Automation For Fair Ethical Business Development: A Single Case Study. *Technological Forecasting and Social Change*, 172. https://doi.org/10.1016/j.techfore.2021.121048

*Margherita, E. G., & Braccini, A. M. (2024). The impact of Industry 4.0 technologies and the soft side of TQM on organisational performance: A multiple case study analysis on manufacturing organisations. *The TQM Journal, 36*(3), 812–831. https://doi.org/10.1108/TQM-01-2022-0022

*Moloney, R., Coffey, A., Coffey, J. C., & Brien, B. O. (2024). Nurses' experiences of working with robotic assisted surgery in an Irish healthcare setting: A qualitative descriptive design. *Nurse Education in Practic, 81*. https://doi.org/10.1016/j.nepr.2024.104183

*Monod, E., Lissillour, R., Köster, A., & Jiayin, Q. (2023). Does AI control or support? Power shifts after AI system implementation in customer relationship man. *Journal of Decision Systems, 32*(3), 542–565. https://doi.org/10.1080/12460125.2022.2066051

*Monod, E., Mayer, A. S., Straub, D., oyce, E., & Qi, J. (2024). From worker empowerment to managerial control: The devolution of AI tools' intended positive implementation to their negative consequences. *Information and Organization, 34*(1), 100498. https://doi.org/10.1016/j.infoandorg.2023.100498

*Moulaï, K., Islam, G., Manning, S., & Terlinden, L. (2022). "All too human" or the emergence of a techno-induced feeling of being less-able: Identity work, able. *The International Journal of Human Resource Management, 33*(22), 4499–4531. https://doi.org/10.1080/09585192.2022.2066982

*Morais, S. P., & Rodrigues, J. C. (2023). The Acceptance of Artificial Intelligence-based Solutions by Store Assistants in Food Retail. *2023 IEEE International Conference on Engineering, Technology and Innovation* (ICE/ITMC), 1–8. https://doi.org/10.1109/ICE/ITMC58018.2023.10332368

Murphy, E. C., & Oesch, D. (2018). Is Employment Polarisation Inevitable? Occupational Change in Ireland and Switzerland, 1970–2010. *Work, Employment and Society, 32*(6), 1099–1117. https://doi.org/10.1177/0950017017738944

Noble, D. F. (1984). *Forces of Production. A Social History of Industrial Automation*. Oxford University Press.

*Papagiannidis, E., Mikalef, P., Conboy, K., & Wetering, R. V. de. (2023). Uncovering the dark side of AI-based decision-making: A case study in a B2B context. *Industrial Marketing Management, 155*, 253–265. https://doi.org/10.1016/j.indmarman.2023.10.003

*Parschau, C., & Hauge, J. (2020). Is automation stealing manufacturing jobs? Evidence from South Africa's apparel industry. *Geoforum, 115*, 120–131. https://doi.org/10.1016/j.geoforum.2020.07.002

Paul, J., Khatri, P., & Kaur Duggal, H. (2024). Frameworks for developing impactful systematic literature reviews and theory building: What, Why and How? *Journal of Decision Systems, 33*(4), 537–550. https://doi.org/10.1080/12460125.2023.2197700

Pfeiffer, S. (2016). Robots, Industry 4.0 and Humans, or Why Assembly Work Is More than Routine Work. *Societies, 6*(2), 16. https://doi.org/10.3390/soc6020016

*Pors, A., & Schou, J. (2021). Street-level morality at the digital frontlines: An ethnographic study of moral mediation in welfare work. *Administrative Theory & Praxis, 43*(2), 154–171. https://doi.org/10.1080/10841806.2020.1782137

*Porter, A. J., & Van Den Hooff, B. (2020). The complementarity of autonomy and control in mobile work. *European Journal of Information Systems, 29*(2), 172–189. https://doi.org/10.1080/0960085X.2020.1728200

*Ranerup, A., & Svensson, L. (2023). Automated decision-making, discretion and public values: A case study of two municipalities and their case management of social assistance. *European Journal of Social Work, 26*(5), 948–962. https://doi.org/10.1080/13691457.2023.2185875

*Schaupp, S. (2022). Cybernetic proletarianization: Spirals of devaluation and conflict in digitalized production. *Capital & Class, 46*(1), 11–31. https://doi.org/10.1177/03098168211017614

*Shestakofsky, B. (2017). Working Algorithms: Software Automation and the Future of Work. *Work and Occupations, 44*(4), 376–423. https://doi.org/10.1177/0730888417726119

*Snell, D., & Gekara, V. (2023). Re-examining technology's destruction of blue-collar work. *New Technology, Work and Employment, 38*(3), 415–433. https://doi.org/10.1111/ntwe.12259

Thompson, P., & Laaser, K. (2021). Beyond technological determinism: Revitalising labour process analyses of technology, capital and labour. *Work in the Global Economy, 1*(1–2), 139–159. https://doi.org/10.1332/273241721X16276384832119

*Van Den Broek, E., Sergeeva, A., & Huysman Vrije, M. (2022). When the Machine Meets t he Expert: An Ethnography of Developing AI for Hiring. *MIS Quarterly, 45*(3), 1557–1580. https://doi.org/10.25300/MISQ/2021/16559

*Van Hoek, R., Gorm Larsen, J., & Lacity, M. (2022). Robotic process automation in Maersk procurement–applicability of action principles and research opportunities. *International Journal of Physical Distribution & Logistics Management, 52*(3), 285–298. https://doi.org/10.1108/IJPDLM-09-2021-0399

*Van Overbeke, T. (2024). (De)regulating automation: The rise of credit scoring and market-led banking in the UK and Germany. *Comparative European Politics, 22*(1), 85–109. https://doi.org/10.1057/s41295-022-00292-7

*Vereycken, Y., Guisset, A., & Ramioul, M. (2024). The same but different: Understanding variation and similarity in the outcomes of a similar technology. A comparative case study on the deployment of manufacturing execution systems in three Belgian SME's. *Information and Organization, 34*(4), 100539. https://doi.org/10.1016/j.infoandorg.2024.100539

Vidal, M. (2022). *Management Divided. Contradictions of Labor Management*. Oxford University Press.

*Viktorelius, M., MacKinnon, S. N., & Lundh, M. (2021). Automation and the imbrication of human and material agency: A sociomaterial perspective. *International Journal of Human-Computer Studies, 145*, 102538. https://doi.org/10.1016/j.ijhcs.2020.102538

*Waizenegger, L., & Techatassanasoontorn, A. A. (2022). When robots join our team: A configuration theory of employees' perceptions of and reactions to Robotic Process Automation. *Australasian Journal of Information Systems, 26*. https://doi.org/10.3127/ajis.v26i0.3833

*Waldman-Brown, A. (2020). Redeployment or robocalypse? Workers and automation in Ohio manufacturing SMEs. *Cambridge Journal of Regions, Economy and Society, 13*(1), 99–115. https://doi.org/10.1093/cjres/rsz027

*Wright, J. (2019). Robots vs migrants? Reconfiguring the future of Japanese institutional elder-care. *Critical Asian Studies, 51*(3), 331–354. https://doi.org/10.1080/14672715.2019.1612765

Imprint

Martin Krzywdzinski
Automation and Work Through a Qualitative Lens:
A Systematic Literature Review of Empirical Research from 2000 to 2024

Weizenbaum Discussion Paper #55
Mai 2026

ISSN 2943-937X \ DOI 10.34669/WI.DP/55

Weizenbaum-Institut e.V.
Hardenbergstraße 32 \ 10623 Berlin \ Tel.: +49 30 700141-001
info@weizenbaum-institut.de \ www.weizenbaum-institut.de

COORDINATION: Dr. Moritz Buchner \ **TYPESETTING:** Luisa Le van, M.A., Atelier Hurra

With funding from the:

Federal Ministry of Research, Technology and Space

BERLIN
Senate Department for Higher Education and Research, Health and Long-Term Care

weizenbaum institut